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Elephant poaching risk assessed using spatial and non-spatial Bayesian models

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ABSTRACT

Bayesian statistical methods are being used increasingly in crime research because they overcome data quality problems that arise due to the covert nature of crime, but the use of such methods is still in its infancy in the field of wildlife poaching—a specific form of crime. We analyzed poaching risk for African elephant (*Loxodonta africana*) by comparing spatial and non-spatial Bayesian models. Reports on elephant poaching in the Tsavo ecosystem were obtained for 2002–2012 from the Kenya Wildlife Service. The ecosystem was divided into 34 spatial units for which poaching data were aggregated and served as the base units for analysis. Spatial and non-spatial Bayesian models were fed with expert knowledge obtained through survey responses from 30 experts. The predictive accuracy of both models was assessed using the Deviance Information Criterion (DIC). Our results indicated that spatial Bayesian modeling improved the model fit for mapping elephant poaching risk compared to using non-spatial Bayesian models (DIC value of 193.05 vs 199.03). The results further showed that the seasonal timing of elephant poaching (i.e., in dry and wet seasons), density of waterholes, livestock density and elephant population density were factors significantly influencing the spatial patterns of elephant poaching risk in the Tsavo ecosystem for both models. Although there were similarities in the high risk areas for elephant poaching recognized in both models, risk probability values per spatial unit could differ. Furthermore, spatial Bayesian modeling also identified areas of high poaching risk that were not predicted by the non-spatial model. These findings provide vital information for identifying priority areas for combating elephant poaching and for informing conservation management decisions. The model we present here can be applied to poaching data for other threatened species.

1. Introduction

Widespread illegal hunting and the bush meat trade occur more frequently and with greater impact on wildlife populations in the Southern and Eastern savannas of Africa than previously thought (Lindsey et al., 2012). For example, in 2011 alone, about 40,000 elephants were poached for their ivory in Africa—equivalent to a species loss of about 3% (Wittemyer et al., 2014). A better understanding of where and when poaching is likely to occur would enable more effective law enforcement and possibly decrease the decline of wildlife due to poaching (Critchlow et al., 2015). Given the covert nature of poaching (Burn et al., 2011) that makes it difficult to record detailed spatial and temporal information on all poaching events, methods are needed that can deal with data scarcity (Gelman and Price, 1999). Not accounting for such scarcity can lead to unstable estimations of poaching patterns (Bernardinelli et al., 1995; Congdon, 2000).

With the ability to incorporate expert knowledge to help inform estimates for poorly sampled areas, Bayesian methods are becoming an increasingly common tool for ecological and disease mapping (Gelman and Price, 1999). In Bayesian statistical methods, crime data is regarded as a fixed quantity, whereas model parameters are considered to be random quantities when the measurement uncertainty is determined. Bayes' theorem combines information

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contained in the data (recorded crime) with prior knowledge to obtain posterior probabilities of crime risk, including risks for those areas that have a crime incidence count of zero (Law and Chan, 2012). The advent of recently developed Bayesian statistical approaches enables associations between crime occurrence and potential risk factors to be analyzed (Law and Chan, 2012; Law and Haining, 2004; Law et al., 2006; Law and Quick, 2013). Although in some situations non-spatial regression models can be carefully implemented to examine such associations (MacNab, 2004), these methods are limited in their ability to handle spatial data in which unmeasured confounders and spatial autocorrelation are evident (Einhorn et al., 1977; MacNab, 2004).

Crime research is increasingly using spatial methods because geocoded crime data and crime-related spatial data are becoming more available, and spatial methods for analyzing crime data at the local level are being developed (Law and Chan, 2012). Spatial analysis at the local level typically takes the form of exploratory spatial analysis such as cluster detection (e.g., hot spot identification) (Rashidi et al., 2015), or confirmatory spatial regression (e.g., risk factor identification) (Law and Quick, 2013).

The spatial association between crime occurrence and potential risk factors has traditionally been modeled using a frequentist (classical) statistical approach in the form of logistic regression (Haines et al., 2012; Nielsen et al., 2004). However, such an approach does not satisfactorily account for local risk factors (i.e., existing in one unit but not in neighboring ones) that remain unknown and are not captured in the model (Law and Chan, 2012). As a result, spatial autocorrelation remains a problem in traditional approaches even if the covariates are adjusted for it (Law and Chan, 2012). Moreover, developing accurate models requires large datasets; this can be a problem in crime research where observational data are scarce, costly to obtain, or subject to design and quality concerns.

Bayesian statistics have been used to fit spatial models in several crime studies (Haining and Law, 2007; Law and Chan, 2012; Law and Haining, 2004; Law et al., 2006; Law and Quick, 2013; Porter and Brown, 2007). However, to our knowledge, few studies have utilized spatial Bayesian methods to explore relationships between wildlife poaching (a specific form of crime) and potential risk factors. One example is Burn et al. (2011), who studied global trends and factors associated with the illegal killing of elephants in Africa and Asia between 2002 and 2009. They used a Bayesian hierarchical modeling approach to estimate the trend and the effects of site- and country-level factors associated with the poaching. At a country level, key determinants for elephant poaching were poor governance and low levels of human development; whereas at a site level they were low human population density and forest cover. Although Burn et al. (2011) explored spatial Bayesian modeling in their analysis, they did not incorporate any informative prior knowledge (expert knowledge) in the model.

Expert knowledge can provide information about model parameters and help characterize uncertainty in models, and it can be useful when data are limited or are not available (Kuhnert, 2011). For example, Murray et al. (2009) used expert judgments to fill information gaps related with species occupancy in unreachable sites. Expert knowledge has also been used to assess the impacts of grazing levels on bird density in woodland habitats (Martin et al., 2005). Furthermore, expert knowledge was used to create Bayesian networks for criminal profiling from limited data (Baumgartner et al., 2008).

Bayesian methods can incorporate expert knowledge through priors (prior knowledge), using probability distributions representing what is known about the effect of the factor on what is being modeled (Gelman et al., 2014; Kuhnert et al., 2010; Stigler, 1986). The priors reflect the knowledge available on model parameters before observing the current data (Schoot et al., 2014; Stigler, 1986). Non-informative priors can be specified if one does not want to impose any prior knowledge on a model. The use of non-informative priors is referred to as objective Bayesian statistics since only the data determine the posterior results (Clarke, 1996; Press, 2009; Schoot et al., 2014). In contrast, informative priors convey information on prior preference for certain parameter values. Methods using informative priors are referred to as subjective Bayesian statistics (Akaike, 1977; Clarke, 1996; De Finetti et al., 1990; Press, 2009; Schoot et al., 2014). Subjective priors are beneficial because findings from previous research and expert knowledge can be incorporated into the analyses (Akaike, 1977; Clarke, 1996; Press, 2009; Schoot et al., 2014). For example, after several studies on the relationship between elephant poaching and risk factors, we may be able to provide a fairly accurate prior distribution of the parameters that measure this relationship. Prior information can also be obtained from expert knowledge gained from extensive experience. Different points of view might represent different priors for parameters, however, it has been shown that Bayesian expert systems are robust with respect to the absolute difference in priors (McCarthy, 2007). For example, Crome et al. (1996) used Bayesian methods to study effects of logging on mammals and birds. They were mainly interested in investigating real differences of opinion, which were elicited from experts. Differences of opinion were represented in the different priors for the impact of logging on mammals and birds. They revealed that these differences of opinion could reach consensus for various species (McCarthy, 2007).

In a previous study, we analyzed elephant poaching hotspots from poaching incidence data using clustering techniques (Rashidi et al., 2015). However, we did not incorporate any knowledge about risk factors nor did we account for the possibility of missing poaching data in the records. In the present study, we propose to use expert knowledge as prior information on risk factors.

A key feature of the spatial Bayesian modeling approach is the specification of the spatial random effect term to the Bayesian non-spatial model; this term can account for unidentified or unexplained sources of spatial autocorrelation. The spatial random effect term includes a spatially unstructured random variable and a spatially structured variable. Spatially unstructured random variables ignore the geographical location of the analysis units, whereas spatially structured random variables assume that geographically proximate spatial units tend to have similar risks (Law and Chan, 2012). Another advantage of the Bayesian spatial model is its capability to account for missing data, where, due to data limitations, the analyst is concerned about the effects of important covariates that are missing (Law and Haining, 2004; Law and Quick, 2013).

Our study aimed to address four questions: (1) Is the Bayesian spatial model more effective for mapping elephant poaching risk than the non-spatial model? (2) What are the key factors influencing elephant poaching risk as determined by Bayesian spatial and non-spatial models? (3) Where are the high risk areas for elephant poaching in the Tsavo ecosystem based on both models? (4) Where are areas of high risk unexplained by the covariates?

2. Materials and methods

2.1. Study area

The Tsavo ecosystem consists of an area of about 38,128 km^2 in south-east Kenya (Fig. 1). It lies between 2 and 4°S, and 37.5–39.5°E. The Tsavo ecosystem has the highest population of elephants in Kenya, and also the highest number of reported elephant poaching incidents (Maingi et al., 2012; Rashidi et al., 2015). The anti-poaching activities in the Tsavo ecosystem face challenges of insufficient human and financial resources, and the extensive area to be covered (Maingi et al., 2012; Rashidi et al., 2015). Several rivers cross the ecosystem, including the Tsavo, Tiva, Galana, Athirivers,

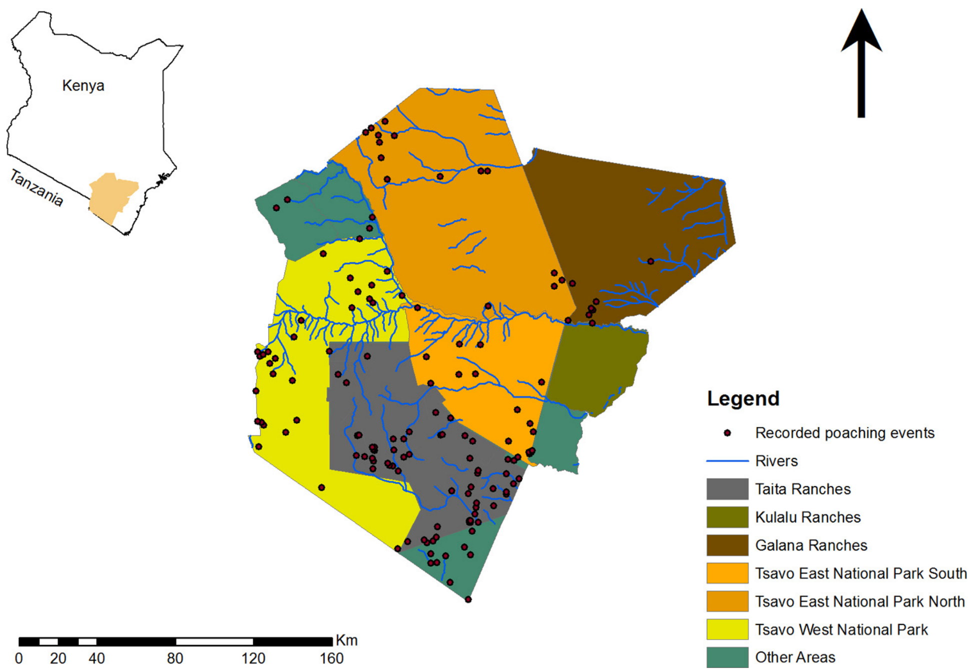

Fig. 1. Location of the Tsavo ecosystem in Kenya. The colors show the different ranches and sections of the Tsavo ecosystem; the dots indicate the recorded elephant poaching locations (2002–2012).

and Voi (Maingi et al., 2012). The study area includes the Tsavo West National Park, Tsavo East National Park North (north of Galana River) and, Tsavo East National Park South (south of Galana River), with the remainder of the area covered by private ranches (Fig. 1). Vegetation in the Tsavo ecosystem is dominated by *Commiphora* shrub savannas (Cobb, 1976) and the climate is semi-arid with a mean annual rainfall varying between 250 and 500 mm, characterized by large spatial and interannual variability. The short rainy season occurs between November and December, when rainfall is concentrated most in the northern and eastern parts, and a long rainy season occurs between March and May (the highest rainfall is between Taita Hills and the Kilimanjaro area) (Leuthold and Leuthold, 1978; Tyrrell and Coe, 1974).

2.2. Block design

To study the probability of elephant poaching between neighboring areas, the study area was divided into 37 blocks, which were initially designed for the aerial counting of the elephant population in the Tsavo-Mkomazi ecosystem (Ngene et al., 2013). They were defined mostly by easily detectable features such as rivers, hills, roads, and protected area boundaries. The average block size was 1098 km^2. The smallest block measured 248 km^2 and the largest block was 2008 km^2 (Ngene et al., 2013). Block numbers 33–35 were excluded because they are located in Tanzania (Rashidi et al., 2015). We used the 34 blocks in the Tsavo ecosystem to differentiate area-level risk probabilities (Fig. 2).

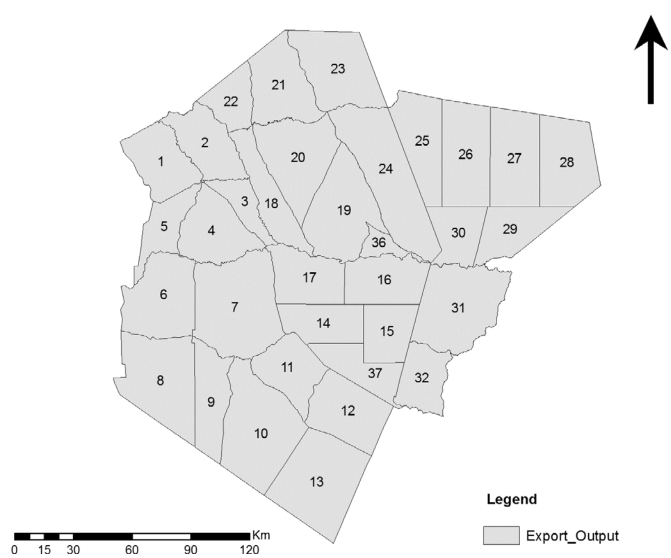

Fig. 2. Numbered blocks for analysis in the Tsavo ecosystem.

2.3. Data

2.3.1. Elephant population and poaching incidence data

The Kenya Wildlife Service (KWS) provided the population and poaching data on elephants for this study. Elephant population data were collected by aerial surveys carried out in the Tsavo ecosystem from 7 to 12 February 2011 (Ngene et al., 2013). Since there were no significant changes in elephant population and distribution from 2002 till 2012 (Ngene et al., 2013), we assumed that the spatial distribution of the elephant population in 2011 could be used for all years. The dataset included the geographic coordinates and names of the locations where elephants were seen, the number of elephants observed at that location, and the dates of observation (Ngene et al., 2013). The poaching incidence data were collected from aerial patrols and daily ground patrols carried out by KWS through the Monitoring the Illegal Killing of Elephants (MIKE) program. Regular patrols and extensive coverage of monitored sites is essential to collect comprehensive data for the MIKE program. Rangers used their bush and tracking skills as well as contacts in the local communities to recognize poachers and poacher trails, as well as visual observations in the field (e.g. presence of vultures) to identify carcass locations. Rangers are expected to complete patrol forms and carcass forms, and to use global positioning system (GPS) units to record locations (CITES, 2010). The dataset listed 151 poaching locations in the study area between June 2002 and August 2012 and included the estimated date of death, geographic coordinates, and names of the locations where elephant carcasses were found.

2.3.2. Risk factors

We selected potential risk factors for poaching based on discussions with experts and previous research (Kyale et al., 2011; Maingi et al., 2012). These factors included: (1) distance to roads, (2) distance to settlements, (3) distance to rivers and streams, (4) density of waterholes, (5) elevation, (6) slope, (7) mean normalized difference vegetation index (NDVI), (8) standard deviation of NDVI, (9) elephant population density, (10) livestock density, (11) distance to international border, and (12) seasonal timing of elephant poaching (i.e., poaching probabilities in the dry and wet seasons). 'Distance to roads' may be important because this would provide easy access and escape opportunities for the poachers (Haines et al., 2012). We modeled 'distance to settlements' as a potential risk factor because the distance-decay concept implies that poaching will tend to cluster where opportunities and motivated offenders are plentiful (Maingi et al., 2012). 'Distance to rivers and streams' may be a potential risk factor because these linear landscape features are places where elephants aggregate, thus hunting pressure may be higher near rivers and streams. Likewise, we can expect poaching to be related to the 'density of waterholes', because these are areas with many elephants. 'Elevation' may add to the risk because of the abundance of browse species favored by elephants at different elevations. 'Slope' could pose a risk because rough terrain can provide cover for poachers. We modeled the mean NDVI and standard deviation of NDVI as potential risk factors because vegetation condition could provide cover for poaching activities. 'Elephant population density' was included as a potential risk factor because we would expect poaching to be concentrated where elephants are most plentiful (Maingi et al., 2012). 'Livestock density' is an important risk factor because it can provide cover for poachers in the form of ranchers and ranches. 'Distance to international border' could be a risk factor because it may allow for easy transportation of the ivory directly to the ivory traders. Finally, we focused on the 'seasonal timing of elephant poaching', which might influence the extent of poaching because in different seasons poaching is likely to occur at different locations due to elephants' requirements such as food, water, or even land cover.

ArcGIS' Spatial Analyst was used to generate the nearest distance (m) from the center of each block to roads, settlements, rivers and streams, and to the border with Tanzania (ESRI, 2011). Elevation and slope of the study area were extracted from a 90-m digital elevation model (DEM) derived from the Shuttle Radar Topographic Mission (SRTM). Time series of the NDVI from SPOT-VEGETATION were obtained through the Flemish Institute for Technological Research as 10-day composites. Mean NDVI corresponds to the NDVI average obtained from a time series of 10-day NDVI composites from November 2002 to November 2012 and was used to summarize annual NDVI values for the period studied. We calculated their average over the 10 years. Standard deviation of NDVI corresponds to the mean annual standard deviation of NDVI, obtained from a time series of 10-day NDVI composites from November 2002 to November 2012. The annual standard deviation provides a measure of the within-year NDVI variation as it is affected by seasonality. The mean and standard deviation of NDVI are a proxy for vegetation condition in the Tsavo ecosystem for the period 2002–2012. Based on an aerial count, data on livestock density were compiled by the World Resources Institute and the International Livestock Research Institute. For each block, we calculated mean values for elevation, slope, mean NDVI, standard deviation of NDVI, and livestock density (Table 1). Seasonal timing of elephant poaching (i.e., dry and wet seasons) was used to take seasonality into account. To quantify the seasonal timing of elephant poaching, of the 151 events recorded between June 2002 and August 2012, we first indicated how many were recorded during the dry season (January, February, June, July, August, September, October) and the wet season (March, April, May, November and December) in each block. Then, the probabilities of elephant poaching were calculated for the dry and wet seasons in each block. The dates of poaching events were obtained from the estimated date of death recorded with each observation.

Table 1
The potential risk factors and their associated mean and standard deviation.

Risk factors	Mean	SD
Distance to roads (m)	6791	6044
Density of waterholes (number per km^2)	0.042	0.056
Distance to rivers and streams (m)	7742	6960
Distance to settlements (m)	19,870	12,400
Elevation (m)	489	256
Slope (degrees)	0.988	0.884
Mean NDVI (no dimension)	0.348	0.072
Standard deviation of NDVI	0.012	0.021
Elephant population density (number per km^2)	0.341	0.316
Distance to international border (m)	77,730	35,090
Probability of elephant poaching in wet season (%)	0.150	0.229
Probability of elephant poaching in dry season (%)	0.614	0.406
Livestock density (number per square kilometer)	31.590	37.804

Table 2
Information elicited from 30 experts on the risk factor's impact on elephant poaching in the Tsavo ecosystem, showing the mean response from the experts and the corresponding precision (the inverse of variance).

	Mean Response	Precision
Distance to roads	0.56	12.17
Density of waterholes	0.73	18.55
Distance to rivers and streams	0.54	8.85
Distance to settlements	0.77	34.60
Elevation	0.32	16.90
Slope	0.30	17.88
Mean NDVI	0.97	0.65
Standard deviation of NDVI	0.97	0.65
Elephant population density	0.52	7.51
Distance to international border	0.65	9.68
Probability of elephant poaching in wet season	0.65	11.07
Probability of elephant poaching in dry season	0.65	11.07
Livestock density	0.74	17.79

2.4. Expert rating of poaching risk factors

Thirty experts from the Kenya Wildlife Service were interviewed based on their knowledge about elephants, their habitat, and poaching. They were asked to score how they thought selected factors would contribute to elephant poaching in the Tsavo ecosystem (Table 2) in order to populate a Bayesian expert system with a priori probabilities (Skidmore, 1989). The terminology was explained to the rangers. The survey required the expert to give each factor a score between 0 and 1, depending on how much they thought the factor contributed. There has been considerable debate in the statistical literature regarding elicitation methods and how they can be used to form prior distributions and inform analyses (Kuhnert et al., 2005; Martin et al., 2005). In our study, since there were no major differences in the expert ratings of poaching risk factors, the equal weighted linear opinion pool (i.e., group average) was used to determine the mean response elicited from the experts. This method is simple and delivers accurate judgments compared with more complex methods (Armstrong, 2001). By taking this opinion pool, we avoided difficulties concerned with rating the comparative 'accuracy' of each expert's opinion on the relationship between poaching and various factors (Einhorn et al., 1977; Martin et al., 2005).

2.5. Modeling strategy and analysis

To analyze elephant poaching risks, we fitted Bayesian non-spatial and spatial models using the statistical software WinBUGS (McCarthy, 2007). WinBUGS is a Bayesian modeling tool which requires the specification of priors on the parameters; these priors were determined through expert knowledge. The prior information specified for each factor is a normal distribution with a mean representing the expert opinion the expert opinion for the model parameter and a precision which is based on the overall expert response for each factor (Kuhnert et al., 2010). Spatial interactions between neighboring areas can be defined using an Intrinsic Conditional AutoRegressive Gaussian distribution (ICAR) (Law et al., 2006). The ICAR distribution is a special case of the general conditional autoregressive (or CAR) distribution, which is used as a prior distribution for spatially structured random effects (Law and Haining, 2004). Under the ICAR specification, the mean of spatial structure for one block depends on the spatial structure of its neighboring blocks (Law et al., 2014). The prior information specified for the spatially unstructured random effect is a normal distribution. Both the precision parameters of spatially unstructured random effect and spatially structured random effect follow a gamma distribution (a, b), where a and b are equal to 0.5 and 0.0005, respectively. This gamma distribution is a prior that would provide a reasonable range for relative risks (Elliot et al., 2000). A sensitivity analysis was performed using a different gamma distribution of parameters 0.001 and 0.001 for testing the sensitivity of results to the choice of prior distributions.

WinBUGS uses Markov chain Monte Carlo (MCMC) algorithms to estimate parameters (McCarthy, 2007). This software takes samples from the posterior distribution by using MCMC methods, a series of random numbers in which the value of each is conditional on the previous number (Kéry, 2010), and finally converging to the required posterior (Law et al., 2006). The idea of this iterative procedure is that with sufficiently many simulated observations, it is feasible to acquire an accurate picture of the distribution (Kim, 2011).

2.5.1. Non-spatial Bayesian modeling

The first method of analysis in this study is a non-spatial Bayesian model. The Tsavo ecosystem was divided into 34 blocks labeled $i = 1, \ldots, n$, where $n = 34$, the total numbers of areas. C_i represents mutually independent and Poisson-distributed poaching counts. We assumed that $C_i \sim P(\lambda_i)$, where the parameter λ_i of the Poisson distribution (P) is the expected value of C_i, exp $[C_i]$.

$$\text{Exp}(C_i) = \lambda_i = E_i \mathrm{r_i} \tag{1}$$

where E_i and r are the area-specific expected count and unknown risk, respectively, of elephant poaching events.

We log-transformed Eq. (1) as follows:

$$\text{Log}[\lambda_i] = \log[E_i] + \log[r_i] \tag{2}$$

$$= \log[E_i] + ß0 + ß_1 \mathrm{x_{1i}} + ß_2 x_{2\mathrm{i}} + \ldots + ß_k \mathrm{x_{ki}} \tag{3}$$

Eq. (3) is a Poisson regression model, where $\log[E_i]$ is an offset term with a regression coefficient of one, $X_{1,i}, X_{2,i}, \ldots,$ and $X_{K,i}$ are observations defined for the explanatory variables of $X_1, X_2, \ldots,$ and X_K for block i, K is the total number of explanatory variables, and $ß$ represents covariate coefficients (Law and Chan, 2012; Law and Quick, 2013). This model, however, has problems estimating the area-specific elephant poaching risk (r_i) and testing for the significance of explanatory variables. The maximum likelihood of $\mathrm{r_i}$ (which is calculated by C_i/E_i,) cannot be calculated if data for C_i are missing or equal to zero. Furthermore, the Poisson model assumption presented in Eq. (4) is not valid when over-dispersion is present (Thogmartin et al., 2004). Over-dispersion occurs when some areas have large counts and other areas have small or no counts (Law and Chan, 2012; Law and Quick, 2013). Accounting for over-dispersion is necessary because its effect on a non-spatial model (see Eq. (3)) is that standard errors of parameter estimates will be underestimated, thus inducing type one errors in the hypothesis testing (Law et al., 2006).

$$\text{Exp}[C_i] = \text{var}[C_i] = \lambda_i \tag{4}$$

Likewise, this relationship may display spatial autocorrelation, representing observations that are not independent, which then need to be accounted for in the spatial structure of the non-spatial model (Law and Quick, 2013).

2.5.2. Spatial modeling

Two Gaussian random effects terms, U_i (spatially unstructured) and S_i (spatially structured), were added to the non-spatial model Eq. (3) to form the spatial model Eq. (5). These terms accommodate any over-dispersion that may be unaccounted for in the non-spatial model Eq. (3) (Law and Quick, 2013; Maingi et al., 2012). Priors for U_i and S_i were determined by an independent normal distribution and the ICAR distribution (Besag et al., 1991), respectively.

$$\text{Log}[\lambda_i] = \log[E_i] + ß_0 + ß_1 \mathrm{x_{1i}} + ß_{2x2i} + \ldots + ß_{kx} \mathrm{k_i} + U_i + S_i \tag{5}$$

The models represented by Eqs. (3) and (5) were fitted to the data using an MCMC simulation approach in the WinBUGS software. For each model, MCMC chains comprising 100,000 iterations with a burn-in of 1000 were found to be sufficient to achieve convergence. The Brook-Gelman-Rubin Diagnostic and Monte Carlo standard error (<5% of the sample posterior standard deviation) helped to ensure sufficient burn-in and iterations. Fitting of this model has been reported in detail in the literature (Haining et al., 2009; Law et al., 2006). Based on Eq. (5), the Bayesian spatial random effect model, the relative risk function, $\mathrm{r_i}$, can be written as

$$r_i = [\exp ß_0]\exp[ß_{1\times 1i}]\exp[ß_2 \times {}_{2i}]\ldots\exp[ß_{kx}\mathrm{k_i}]\exp[U_i]\exp[S_i] \tag{6}$$

The DIC was used to evaluate model fit and measure the relative performance of models (McCarthy, 2007). The DIC is a Bayesian equivalent of the Akaike Information Criterion (AIC). The DIC compares model fit without predetermining the number of model parameters, whereas AIC is a penalized likelihood ratio model-choice criterion, where the penalty is the number of parameters in the model (Law and Chan, 2012; Law and Quick, 2013). Smaller values for the DIC indicate a better model fit; the difference should be at least 5 for concluding the model fit is better because Monte Carlo sampling errors inherent in the calculation of DIC need to be accounted for (Law et al., 2014). The DIC is defined by Eq. (7), where $\overline{D}$ is the deviance when using the mean of the posterior distributions for the parameters, $_{PD}$ is the number of effective parameters in the model, $\overline{\theta}$ is the posterior mean of the parameters, and $D(\overline{\theta})$ is the deviance of the posterior means. It is obtained by using the posterior means of the relevant parameters (Law and Quick, 2013; Spiegelhalter et al., 2002).

$$\text{DIC} = \overline{D + p_D} = D(\bar{\theta}) + 2_{PD} \tag{7}$$

2.6. Analysis of risk factors

The most significant explanatory factors related to elephant poaching were identified using the Bayesian spatial and non-spatial models (see Eqs. (3) and (5)). First, a set of explanatory variables used to fit Eq. (3) was identified from Table 1 after accounting for the effects of multicollinearity. Eq. (3) was then fitted with the set of 'non-highly correlated' explanatory variables identified, and

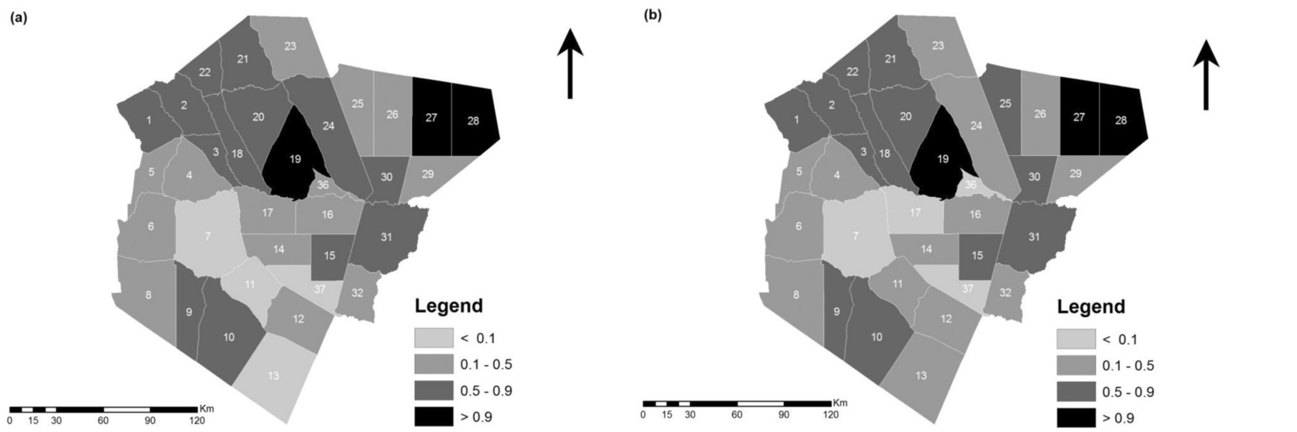

Fig. 3. Tsavo ecosystem displaying the probability of elephant poaching risk for each block: (a) Bayesian non-spatial model and (b) Bayesian spatial model.

those variables that were found significant were used to fit Eq. (5). Explanatory variables that remained significant from the fitting of Eq. (5) were identified as significant risk factors (Law and Quick, 2013).

In the presence of potential multicollinearity between the selected explanatory variables of Table 1, the estimated regression coefficients would tend to have larger sampling variability (Law and Chan, 2012; Law and Quick, 2013). The problem of multicollinearity in the statistical inference of a multiple regression equation can be tackled by calculating a variance inflation factor (VIF) for a set of variables and excluding the highly correlated variables from the set through a stepwise procedure (Dormann et al., 2013; Naimi, 2013). VIFCOR was used to exclude highly collinear variables in Table 1 through a stepwise procedure. VIFCOR is a method based on the calculated VIF statistics. VIFCOR works by looking for the pair of variables that has the maximum linear correlation, and removes the variable which has the larger VIF, replicating the procedure until there is no variable pair with a high coefficient of correlation (Naimi, 2013). Here, we first selected variable pairs that had a linear correlation coefficient greater than a threshold of 0.5. For the variable pair with the highest correlation, one of the variables was excluded, i.e. the one with the highest VIF. The procedure was repeated until no variable pair with a correlation coefficient above 0.5 remained (Naimi, 2013). The variables left were then used to fit Eqs. (3) and (5) separately. By comparing the DIC values (the smaller the DIC, the better the model fit) from these two equations, we identified which model performed better. If any of the explanatory variables were deemed insignificant by our modeling framework, the improved model was re-fitted using only those explanatory variables that were significant to form the final model (Law and Quick, 2013).

3. Results

Among the selected variables (Table 1), distance to road, waterhole density, elephant population density, distance to rivers and streams, seasonal timing of elephant poaching (i.e., probabilities in dry and wet seasons), distance to international border, standard deviation (STD) of NDVI, and livestock density remained after accounting for multicollinearity (Table A.1). The non-spatial analysis (Eq. (3)) revealed that distance to road, distance to rivers and streams, standard deviation of NDVI, and distance to international border were insignificant at the 95% credible interval among those variables that remained after accounting for multicollinearity (Table 3). Therefore we ignored them in further analysis. The inclusion of zero values within the 95% Bayesian credible intervals implies the insignificance of the estimates (Jianmei, 2014).

Table 3
Posterior summaries for ß coefficients of the explanatory variables in Bayesian non-spatial and spatial models.

Explanatory variables	Non-spatial model mean ß (credible interval: 2.5%, 97.5%)	Spatial model mean ß (credible interval: 2.5%, 97.5%)
Probability of elephant poaching in wet season	1.05 (0.78, 1.36)	0.83 (0.42, 1.22)
Probability of elephant poaching in dry season	0.92 (0.55, 1.31)	1.01(0.57, 1.48)
Livestock density	0.20 (0.02, 0.37)	0.56 (0.22, 0.94)
Waterhole density	0.30 (0.07, 0.52)	0.64 (0.28, 1.03)
Elephant population density	−1.75 (−2.03, −1.49)	−0.88 (−1.40, −0.31)
Distance to nearest road	0.10 (−0.01, 0.22)	NA
Distance to rivers and streams	0.05 (−0.14, 0.26)	NA
Standard deviation (STD) of NDVI	0.08 (−0.13, 0.30)	NA
Distance to international border	0.03 (−0.27, 0.21)	NA
DIC	199.03	193.05

NA not applicable, DIC Deviance Information Criterion.

We then ran Bayesian spatial analyses (Eq. (5)) with those variables that were found significant in the Bayesian non-spatial model (Table 3). The result obtained from Eq. (5) revealed that the seasonal timing of elephant poaching, density of waterhole, livestock density, and the elephant population density were significant factors that influence the spatial patterns of elephant poaching risk in the Tsavo ecosystem (Table 3). The Bayesian spatial model had a better model fit than the non-spatial model with a DIC of 193.055 versus 199.03 (Table 3).

Fig. 3 presents the elephant poaching risk probabilities for each block using the non-spatial model (a) and the spatial model (b). The blocks with the highest poaching risk are those that have probabilities greater than 0.9 and the lowest risk blocks are those with probabilities <0.1. While similar spatial patterns of high poaching risk were found in both models, eight blocks displayed different probability classes (blocks 11, 12, 13, 17, 23, 24, 26, and 36).

The map of spatially structured random effects displayed in Fig. 4 indicates the locations of clusters for a high risk of elephant poaching that could not be explained by the factors in the model. When exp (S) (Eq. (6)) is <0.5, it represents a decrease in elephant poaching risk by the unexplained spatial structure in those areas. When exp (S) is >0.5, it represents an increase in risk by the unexplained spatial structure. These areas have a high risk of elephant

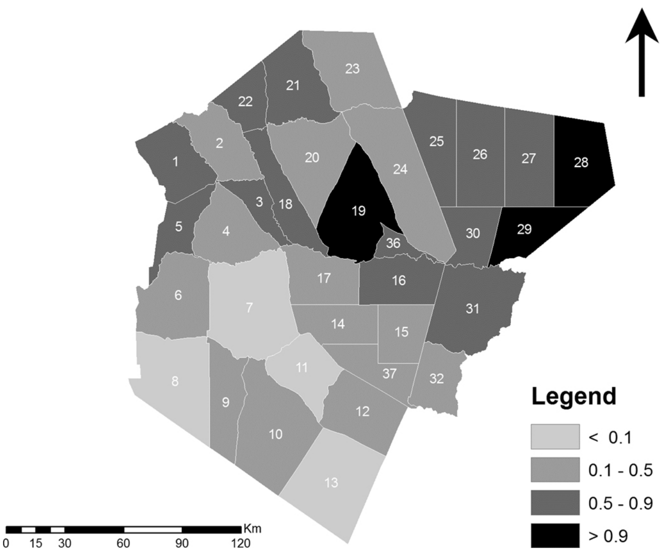

Fig. 4. Areas of high elephant poaching risk that were unexplained by the measured risk factors, i.e., using the spatial model in which the spatial random variable is acting as a proxy of the unmeasured risk factors that were spatially structured.

poaching that is unexplained by the measured variables and their confounding effects.

4. Discussion

Under the common conditions where unmeasured confounders and spatial autocorrelation were evident, Bayesian spatial modeling gave a better model fit for analyzing elephant poaching data than Bayesian non-spatial modeling. One reason for this could be the inherent clustering of poaching activities in geographical spaces (Kyale et al., 2011; Maingi et al., 2012; Rashidi et al., 2015). Poaching tends to be concentrated around some common areas which hold a good potential for poaching activities. Most of the poaching clusters are neighborhoods with similar environment characteristics. As a result, the risks of elephant poaching for areas with zero counts was estimated by borrowing information from areas through the spatial random effect term and with a neighboring structure defined in the Bayesian spatial model (Law and Chan, 2012; Law and Quick, 2013).

When there is spatial structure in the dependent variable (elephant poaching) that could not be described by the selected factors, the non-spatial model ignores the unexplained structure and overestimates the effects of the covariates. In contrast, in the spatial model, the spatial random variable acts as a surrogate of the missing covariates (unmeasured risk factors) that are spatially structured (Law and Chan, 2012; Law and Quick, 2013). As a result, compared with Bayesian non-spatial modeling, the spatial modeling demonstrated an improved model fit through a lower DIC and excluded four significant independent variables that had been identified in the non-spatial model (Table 3).

The results using Bayesian non-spatial modeling indicated that a seasonal timing of elephant poaching (i.e., in the dry and wet seasons), density of waterholes, livestock density, and the elephant population density were the key determinants of elephant poaching. Waterhole density may be explained by elephants' preference for water, i.e., where elephants aggregate makes them more vulnerable to poaching. The elephant population is a significant factor because this likely provides the poachers with the highest harvest related to their effort. This finding supports this idea that poaching risks are higher in areas with a high elephant population (Kyale et al., 2011; Maingi et al., 2012). The influence of livestock on elephant poaching can be explained by the fact that poachers may use livestock as a cover for elephant poaching, either directly or with the assistance of livestock herders. The seasonal timing of elephant poaching was also determined to be a significant explanatory variable of elephant poaching. This partly explains why poaching is more likely to occur in different locations in the dry season than the wet season. The suitability of the natural environment for poaching varies in different locations for different seasons and can be linked to elephants' requirements such as food, water, or even land cover for hiding (Osborne, 2000).

The probability relative risk map allows high and low risk areas to be identified (Fig. 3). This map provides information about the elephant poaching risks in each block and in its neighbors. The different results from the non-spatial and final spatial model can largely be explained by the covariates— the spatially structured or unstructured random effects terms. Areas with a relative risk of poaching >0.50 should be further investigated as elephant poaching hotspots. Methods for detecting elephant poaching hotspots have been described previously, specifically in Rashidi et al. (2015), who detected hotspots using exploratory spatial analysis. They identified hotspots using different spatial and spatiotemporal clustering models; however, the results from this current study not only cover all their detected hotspots, but could also be used to estimate the probability of an area being a hot or cold spot. Moreover, some new areas were detected as hot spots (Fig. 3). One reason for these discrepancies could be because in cluster techniques, as described by Rashidi et al. (2015), the number of poaching incidents detects clusters using the maximum likelihood method. They identified areas of significant clusters, but the technique cannot map the probability of clustering across areas (e.g. in areas not classified as 'clustered').

The map of spatially structured random effects (Fig. 4) reveals the locations of clusters of high risk for elephants that could not be explained by the covariates of factors in the model. This indicated that one or more risk factors (covariates) with spatial structure, which are typically unobserved variables, might be missing in the model (Law and Chan, 2012). These missing risk factors should have little or no connection with the associated factors used in our study (Law and Quick, 2013). Our analyses have not included these factors, which would need to be integrated in a different way. For example, a moonlight factor, which it is not possible to integrate in the model like other variables, or similarly, those variables that were excluded from our analysis under the terms of access to data. For instance, we excluded distance to park offices, park gates, patrol bases and outposts since we could not get data on these factors because of security issues. Moreover, our final model contains all of the factors that are significant after accounting for multicollinearity. One good reason for using the spatial model is that when risk factors that have spatial structure are missing or unidentifiable, the spatially structured random effects term acts as a surrogate for these covariates (Law et al., 2006). This reduces the effects of overestimating the significance of the risk factors in the model or of retaining risk factors in the model that are not actually significant.

5. Conclusions

This study compared a spatial and non-spatial Bayesian model to investigate elephant poaching risk in small areal units (blocks) in the Tsavo ecosystem, Kenya. The models were fitted using a Bayesian simulation approach, which provided a flexible framework for specifying expert knowledge and fitting complex spatial models that would have been difficult to fit with frequentist approaches.

Our results indicated that the seasonal timing of elephant poaching (i.e., dry and wet seasons), density of waterholes, livestock density, and the elephant population density were significantly and consistently identified as key factors that influence the spatial patterns of elephant poaching risk in the Tsavo ecosystem, Kenya. A non-spatial Bayesian model initially ran with nine significant explanatory variables; however, when we added spatially structured and unstructured random effects terms to this equation, only five variables remained significant. As demonstrated by a smaller DIC value, the spatial Bayesian model fitted the data better than the non-spatial model.

Our results have several practical implications. The KWS can use them to allocate financial and human resources effectively to patrol against poaching activity more efficiently in areas with high risks. Furthermore, our results provide vital information for conservation decision-making and management so that more attention can be given to certain areas, for example those with a relative risk of elephant poaching >0.5. Our findings may be useful in identifying priority areas for elephant poaching prevention. In a wider sense, the model we present here can be applied to poaching data for other threatened species.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolmodel.2016.08.002.

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